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A Robust Cattle Identification Scheme Using Muzzle Print Images

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***Abstract*—Cattle identification receives a great research attention as an important way to maintain the livestock. The identification accuracy and the processing time are two key challenges of any cattle identification methodology. This paper presents a robust and fast cattle identification scheme from muzzle print images using local invariant features. The presented scheme compensates some weakness of ear tag and electrical-based traditional identification techniques in terms of accuracy and processing time. The proposed scheme uses Scale Invariant Feature Transform (SIFT) for detecting the interesting points for image matching. For a robust identification scheme, a Random Sample Consensus (RANSAC) algorithm has been coupled with the SIFT output to remove the outlier points and achieve more robustness. The experimental evaluations prove the superiority of the presented scheme as it achieves 93.3% identification accuracy in reasonable processing time compared to 90% identification accuracy achieved by some traditional identification approaches.**

I. Introduction

RECENTLY, governments pay a great attention to the livestock by providing vaccination against the most of diseases. They seek to overcome some food problems and keep the livestock as huge as possible. Cattle identification plays an important role in controlling the disease outbreak, vaccination management, production management, cattle traceability, and cattle ownership assignment [1]. Traditional cattle identification methods such as ear notching, tattooing, branding, or even some electrical identification methods such as Radio Frequency Identification (RFID) [2] are not able to provide enough reliability to the cattle identification due to theft, fraudulent, and duplication. Therefore, the need to a robust cattle identification scheme is a vital requirement.

Human biometrics is a key fundamental security mechanism that assigns unique identity to an individual according to some physiological or behavioral features [3], [4]. These features are sometimes called as biometrics modalities, identifiers, traits, or characteristics. Human biometrics identifiers must fulfill some operational and behavioral characteristics such as uniqueness, universality, acceptability, circumvention, and accuracy [5].

Adopting human biometric traits into animals is a promising technology for cattle identification domain. It has many applications such as cattle classification, cattle tracking from birth to the end of food chain, and understanding animal diseases trajectory and population. On the other side, using animal biometrics in computerized systems faces great challenges with respect to accuracy and robustness as the animal movement can not be easily controlled. Driven from this perspective, adopting human biometrics to cattle identification can overcome plenty of the current cattle identification weaknesses.

Muzzle print, or nose print, was investigated as distinguished pattern for animals since 1921 [6]. It is considered as a unique animal identifer that is similar to human fingerprints. Paper-based or inked muzzle print collection is inconvenient and time inefficient process. It needs special skill to control the animal and get the pattern on a paper. Furthermore, the inked muzzle print images do not have sufficient quality, and hence, it is difficult be used in a computerized manner [7]. Therefore, there is a lack of a standard muzzle print benchmark. Driven from this need, the first contribution of this research is to collect a database of live captured muzzle print images that works as a benchmark for evaluating the proposed cattle identification scheme.

A local feature of an image is usually related to a change of an image property such as texture, color, and pixel intensity [8]. The advantage of local features is that they are computed at multiple points in the image, and hence, they are invariant to image scale and rotation. In addition, they do not need further image pre-processing or segmentation [9]. Scale Invariant Feature Transform (SIFT) [10] is one of the popular methods for image matching and object recognition. SIFT features have been used by some researchers in human biometrics with applications on fingerprints [11], [12] and palmprints [13]. SIFT efficiently extracts robust and unique features, therefore it has been used to overcome different image degradation factors such as noise, partiality, scale, and rotation.

The identification accuracy is the foremost important fac-

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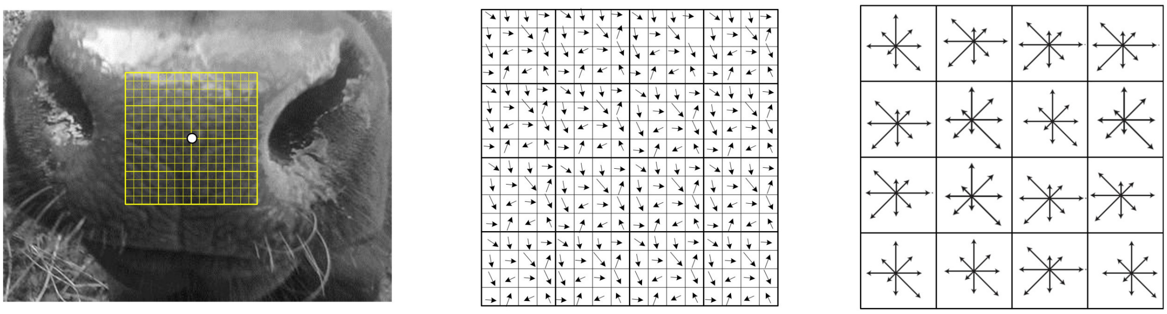

(a) (b) (c)

Fig. 1. The process of building a single SIFT keypoint descriptor: (a) A Single SIFT keypoint extracted from muzzle print image, (b) A 16 × 16 pixel orientations, (c) A single 4 × 4 cells descriptor with 8 pixel orientations. The default length of a single SIFT keypoint descriptor is 4 × 4 × 8 = 128 element.

tor for measuring the performance of any automatic cattle identification approach. This paper presents a robust cattle identification scheme that uses SIFT features for calculating the similarity score between the input muzzle print image and the template one. The superiority of the proposed scheme is the assured cattle identification robustness provided by combining the robust SIFT features with a RANdom SAmple Consensus (RANSAC) algorithm for robust SIFT features matching [14].

The reminder part of this paper is organized as follows: Section II covers some preliminaries topics. Section III explains the design and the implementation of the proposed scheme. Section IV shows the evaluation phase of the proposed scheme. Conclusions and future work are written in Section V.

II. Preliminaries

A. SIFT Features

The SIFT feature extraction works through sequential steps of operations. These steps can be summarized as scale space extrema detection, keypoints localization, keypoint orientation assignment, and building the keypoints descriptor [15]. The Difference-of-Gaussian (DOG) is used to detect the keypoints as the local extrema of DOG function. The pixel is compared against 26 neighboring pixels (8 in the same scale, 9 in the above scale, and 9 in the below scale) to detect the local pixel extrema and minima. Following on, the detected keypoint is localized by determining its neighborhoods, and examine them for contrast and edge parameters. The keypoints with low contrast and weak edge responses are rejected. The keypoint neighborhoods region is used to build the histogram of the local gradient directions, and the keypoint orientation is calculated as the peak of the gradient histogram [10], [15], [16]. The default SIFT feature extraction produces keypoint associated with a descriptor of 128 element length. The descriptor is constructed from (4 × 4 cells) × 8 orientations [17]. The cascaded operations of building a single SIFT keypoint descriptor from muzzle print image are shown in Fig. 1.

Applying SIFT feature extraction translates the muzzle print image into a set of keypoints according to the local maxima. The extracted keypoint is associated with a descriptor related to the orientations of the surrounded pixels. In this paper, a standard SIFT extraction has been used for keypoint detection and building the associated descriptor. SIFT features have been extracted and matched using the VLFeat library [18]. The output of matching process is a similarity score between the input image and the template that is enrolled in the database.

B. Identification Accuracy

In order to measure the accuracy of the presented cattle identification scheme, The identification *Error Rate* (*ER*) is considered. The ER is defined as “the rate that the identified animal, the animal who corresponds to the template image, is different from the animal of the input image”. We also consider the standard verification error rates as FAR, FRR, and ERR [19]. The *False Acceptance Rate* (*FAR*) is the rate that the similarity between the images of different animals is greater than a threshold. Whereas the *False Rejection Rate* (*FRR*) is calculated as the rate that the similarity between two images of the same animal is less than a threshold. Thus, the FAR and FRR depend on the similarity threshold. The *Equal Error Rate* (*EER*) is the value of FRR and FAR at the point of the threshold where the two error rates are identical [20].

III. Proposed Identification Scheme

Analogy to the human fingerprints, cattle muzzle prints have some discriminative features according to the grooves, or valleys, and beads structures. These uneven features are distributed over the skin surface in the cattle nose area. These features are defined by the white skin grooves, or by the black convexes surrounded by the grooves [7], see Fig. 3 for consulting the convexes and the grooves in muzzle print images taken from two different animals.

Minagawa et al. [7] used the joint pixels on the skin grooves as a key feature for muzzle print matching. Some long preprocessing steps were conducted to extract the joint pixels. This approach achieved maximum and minimum matching scores as 60% and 12%, respectively. It achieved unsatisfactory identification performance (accuracy) that was around 30% measured over a database of 43 animals.

Noviyanto and Arymurthy [21] applied Speeded-Up Robust Features (SURF) on muzzle print images for enhancing the identification accuracy. A U-SURF method was applied on 8

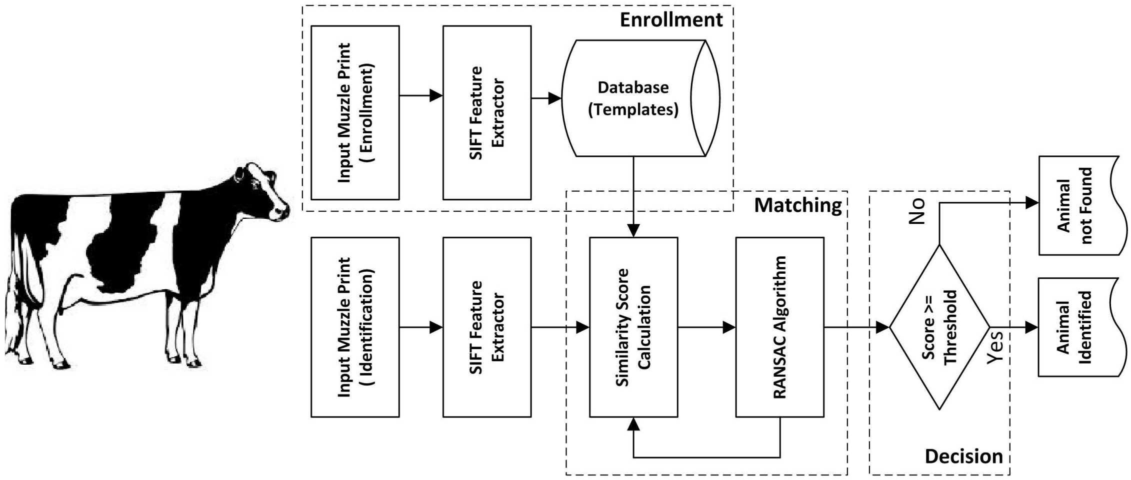

Fig. 2. A block diagram of a complete cattle identification system using muzzle print images. The components of the enrollment phase and the identification phase are emphasized in the block diagram. The proposed identification scheme is represented as a combination between SIFT features and RANSAC algorithm.

animals with 15 images each. The experimental scenario used 10 muzzle print images in the training phase, and the other 5 images were used as input samples. The maximum achieved identification accuracy under rotation condition was 90%.

The presented scheme in this research is robust from two perspectives. First, it invests the robustness of the SIFT features to image scale, shift, and rotation. Second, it uses the RANSAC algorithm as a robust inliers estimator for enhancing the matching results of SIFT features, and ensure the robustness of the matching process. The proposed scheme includes SIFT feature extraction, SIFT feature matching, and RANSAC algorithm. Fig. 2 shows a generic and complete muzzle print based cattle identification system, and highlights the cascaded components of the presented scheme.

RANSAC algorithm has been developed by Fischler and Bolles [14] especially for computer vision, and it works as robust estimator for features matching. In many images matching cases, RANSAC is an effective robust estimator, which can handle around 50% mismatch contamination levels of the input samples. The integration of the extracted local invariant features and RANSAC is valuable for optimizing the images similarity score measurement using SIFT features [22].

Admittedly, the generic animal identification system, shown in Fig. 2, works the same way of the human identification one. It has two phases; enrollment phase and identification phase. In the enrollment phase, a muzzle print image is presented and the SIFT feature vector is constructed. Then, the extracted feature vector is stored as a template in the database. The identification phase includes the same enrollment procedure plus matching and decision sub-phases. For calculating the similarity score, the SIFT features of the input image is matched against the templates stored in the database as (1:N) matching procedure. The muzzle print image corresponding to the feature vector that has a shortest distance to the input feature vector is considered as the most similar one, and it is given the highest similarity score. RANSAC homography algorithm comes at the end of the matching process to remove the matching outliers, mismatched SIFT keypoints, data and ensure the robustness of the similarity score. The animal identity is then assigned according to the highest estimated similarity score between the input image and the template one.

IV. Performance Evaluation

The experiments in this paper have been conducted using a PC with Intel® Core™ i3-2120 running at 3.30 GHz, and 8 GB of RAM. The PC is empowered by Matlab® and Windows® 64-bit. The VLFeat library [18] has been used for extracting, processing, and matching the SIFT features. VLFeat has been installed and optimized for the mentioned experimental environment.

A. Database

The lack of a standard muzzle print images database was a challenge for conducting this research. Therefore, collecting a muzzle print images database was a crucial decision. The database has been collected from 15 cattle animals with 7 live captured muzzle print images each. A sample of muzzle print images captured from two individual animals is shown in Fig. 3. A special care has been given to the quality of the collected images. The collected images cover different quality levels and degradation factors such as image rotation and image partiality for simulating some real time identification conditions.

The identification scenario works as follows: 7 images of each animal have been swaped between the enrollment phase an identification phase, and the similarity scores between all of them are calculated. Therefore, similarity score matrix with dimension of 105 $\times$ 105 have been created. The animal is correctly identified if the similarity score between the input sample and the template samples is greater than or equal a specific threshold. The template of a single animal has been constructed from 6 images which were marked as $T_1, T_2, T_3, ..., T_6$. The remaining 1 image has been used as

Fig. 3. A sample of the collected muzzle print images database from live animals. The represented muzzle print images have been taken from two different animals. The muzzle print images show different deteriorating factors include orientated images, blurred images, low resolution images, and partial images.

input, and was marked as I_1, S was a similarity function, and H was a similarity score. A correctly identified animal should strictly following the next equation as:

$$S(I_1, T_1) \parallel S(I_1, T_2), ..., \parallel S(I_1, T_6) \geq H \quad (1)$$

The FAR, FRR, and ERR have been calculated according to the criteria mentioned in Section II-B.

B. Evaluation Results

Preceding to any experimental work, the database images have been processed in terms of image enhancement, image segmentation, and image normalization. The first experimental scenario is directed toward setting the best SIFT parameters that compromise the number of extracted features (keypoints) with the consumed processing time. The preparatory experiments showed that the most effective parameter is the peak threshold (`PeakThresh`) [15], [18], thus the objective of this scenario is to optimize the peak threshold. The results of the conducted experiments is shown in Fig. 4. The reported results are the average of value of 105 feature extraction processes and 5565 matching operations. The maximum number of features is achieved with (`PeakThresh = 0.0`), however with (`PeakThresh = 0.001`), the extracted features are reduced by 30, and the extraction time is reduced by 5 ms. The other `PeakThresh` values achieve unacceptable number of features regardless of the time factor. The optimum `PeakThresh` value is selected as 0.0 seeking for more SIFT features, and hence, more robustness in feature matching. Following on, the SIFT peak threshold is set to that optimum value, whereas the other parameters were kept as defaults.

In real time identification, 6 images of each individual animal have been processed and enrolled in the database, the

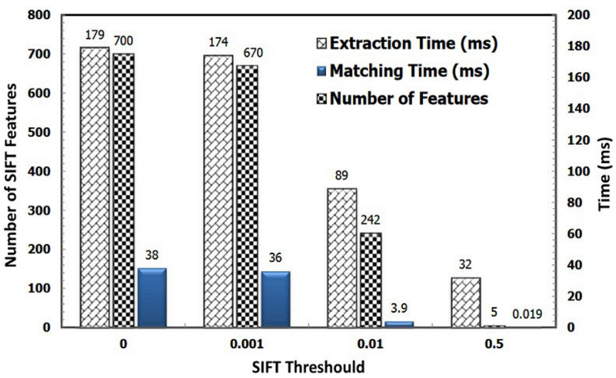

Fig. 4. The behavior of SIFT feature extraction with different peak threshold (`PeakThresh`) values with respect to the number of features, the extraction time, and the matching time. The optimum value is `PeakThresh = 0.0`.

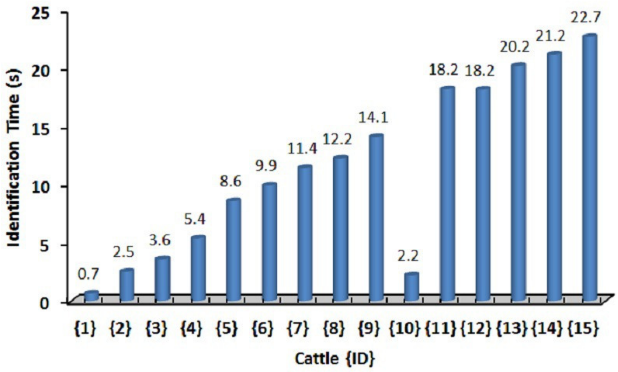

Fig. 5. The identification time for each input animal. Due to the linear search approach, the identification time linearly increases as the order of the template inside the database increases. The cattle with ID $\{10\}$ is wrongly identified.

TABLE I
THE INPUT IMAGES, THE MATCHED IMAGES, THE MATCHING SCORES, AND THE IDENTIFICATION STATUS FOR THE IDENTIFICATION SCENARIO.

Input Image	Matched Image	Matching Score	Identification Status
101_5	101_3	71.56	Correct
102_5	102_4	45.45	∼
103_5	103_1	73.33	∼
104_5	104_1	42.00	∼
105_5	105_7	45.00	∼
106_5	106_3	51.85	∼
107_5	107_3	87.77	∼
108_5	108_1	48.00	∼
109_5	109_3	95.37	∼
110_5	**102_3**	**45.76**	**False**
111_5	111_7	39.00	Correct
112_5	112_1	70.37	∼
113_5	113_3	89.59	∼
114_5	114_1	57.14	∼
115_5	115_1	50.00	∼

total images in the database were ($6 \times 15 = 90$), and 1 image has been used as input to simulate the identification operation. According to equation 1, 14 animals out of 15 have been correctly identified which achieves equivalent identification accuracy value as 93.3%. It is worth notice that the average consumed feature extraction time is 179 ms and the average individual matching time is 38 ms including RANSAC optimization, which are consistent with Fig. 4. However, both times are considered very short for single feature extraction and matching operation, the total identification time still long, around ≈ 23 s at maximum, because a linear database research method has been used, and the identification time is based on the location of the template inside the database. The identification time of each input animal is shown in Fig. 5.

Table I summarises outcomes of the conducted real time identification phase in terms of the input image, the matched template image, the matching score, and the status (correctness) of the identification operation. The image naming scheme works as $1XX\_Y$, whereas XX is the cattle ID (1 to 15), and Y is the image order (1 to 7). The Table shows that the cattle with ID $\{10\}$ is wrongly identified because the similarity score with a template image from cattle ID $\{2\}$ is greater than the defined threshold. The reported results in the Table are consistent with Fig. 5 as the wrongly identified animal consumes very short identification time, and violates the linearity of the incremental identification time with the increased cattle ID.

The wrongly identified animal is considered as false matched or false accepted input because the match occurred with a template that does not correspond to the input sample. The FAR in this case is 6.67%, and it is equal to the identification ER. The relations between FAR, FRR, and ERR are determined according to the similarity threshold. Fig. 6 shows FAR versus FRR related to the similarity threshold. In order to achieve FAR equal to 6.67%, the similarity threshold should be selected around 45. However, the conducted experiments showed that FAR equals to 6.67% has been achieved with a threshold equals to 39, and with FRR equals to 0. We do believe that this is because of combining multiple images from the same animal in one database template.

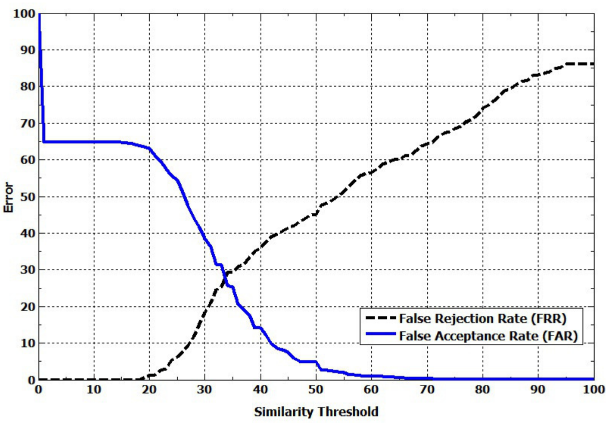

Fig. 6. False Acceptance Rate (FAR) and False Rejection Rate (FRR) plotted versus the similarity threshold. The Equal Error Rate (ERR) is shown as the cross point between FAR and FRR. ERR is ≈ 27.4 with threshold is ≈ 34.0.

V. Conclusions and Future Work

This paper has presented a robust cattle identification scheme that uses muzzle print images as input to SIFT feature extraction and matching. Due to the lack of standard muzzle print database, we have collected 105 images from 15 animals to work as a benchmark for the presented scheme. In order to evaluate the robustness of the scheme, the collected images cover different deteriorating factors such as rotated images, blurred images, partial images, and low resolution images. The achieved identification accuracy is 93.3% compared to 90% reported in the literature. The superiority of the presented scheme comes from the coupling of local invariant features with RANSAC homography as a robust outliers removal algorithm. Muzzle print images database extension and standardization for international benchmark of muzzle print related algorithms is one of the future work. Additionally, the reduction of the identification time in a large database is an interesting challenge that will also be tackled in the future.

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